# Emotional Parameters in Cognitive Architecture: Examination Through Simple Memory Performance

**Kohei Shimbori (shimbori.kohei.21@shizuoka.ac.jp)**
**Masaru Shirasuna (shirasuna-m@inf.shizuoka.ac.jp)**
**Junya Morita (j-morita@inf.shizuoka.ac.jp)**
Department of Informatics, Graduate School of Integrated Science and Technology, Shizuoka University,
3-5-1, Johoku, Chuo-ku, Hamamatsu, Shizuoka, 432-8011, Japan

## Abstract

A key challenge in cognitive modeling is capturing how emotional states modulate internal cognitive parameters. While cognitive architectures such as ACT-R (Adaptive Control of Thought-Rational) provide a principled framework for simulating memory and decision-making, their emotional components remain underexplored. This study examines how individual differences in emotional states, particularly anxiety and affective valence, are reflected in core memory-related parameters of ACT-R. Across two experiments using a digits recall task, we introduced emotional variation via affective stimuli and applied a model-fitting procedure to estimate individual values for the mismatch penalty and activation threshold. Results from the second experiment revealed significant correlations between state anxiety and both parameters, suggesting that emotional traits systematically shift memory retrieval dynamics. Our findings offer empirical support for integrating emotion into cognitive architectures without introducing ad hoc modules, and contribute to broader efforts to align the Common Model of Cognition with affective science. This work highlights the potential of inverse modeling as a tool for understanding the emotion–cognition interface and opens new avenues for modeling individual differences in affect-sensitive cognitive systems.

**Keywords: cognitive architecture, ACT-R, emotion–cognition interaction, parameter estimation, memory recall, state anxiety, individual differences**

## Introduction

In the tradition of cognitive science research, computational models that approximate human cognition have been a main target of study and utilized widely for simulations in order to understand human internal processes. Recent progress of this approach includes attempts to estimate parameters that control the behavioral tendencies of models in accordance with individual human data (Kangasrääsiö, Jokinen, Oulasvirta, Howes, & Kaski, 2019). Such attempts not only have practical significance in that they can predict performance on arbitrary cognitive tasks by constructing models tailored to individuals, but are also important for understanding internal mechanisms as relationships between objective parameters.

However, previous studies have mainly estimated parameters with little intra-individual variability, such as processing speed (i.e., thinking speed) and memory decay, but the estimation of parameters related to emotional states is rare and has not been sufficiently investigated. Emotional states (affects or feelings)[1], which have large intra-variability, have a significant influence on cognitive processes, and clarifying the relationship between emotional states and cognition in a cognitive model is expected not only to provide a deeper understanding of the human internal mechanisms but also to provide insights into the control of emotional states, leading to the improvement of the daily communication and the clarification of emotion-related behaviors.

This study examines whether the parameters of a cognitive model correspond to individual attributes and subjective feelings, and what kind of relationship exists between them. For these purposes, we will conduct an experiment using the following procedures.

1. Acquire data on cognitive tasks by individual participants.
2. Perform simulations on the cognitive task.
3. Estimate model parameters for each participant by maximizing the fit between the data obtained in the above two steps.
4. Examine the correlation between the estimated parameters and subjective ratings of emotional states.

In this paper, we present two experiments. The first experiment is a preliminary one to collect errors in a simple digits recall task by crowdsourcing, and tried to find correlations between estimated parameters and subjective ratings. Following the results obtained in the first experiment, the second experiment was conducted to improve the procedure of the first experiment to obtain more precious emotion-related errors and ratings. Before explaining these results, we review the related studies that provide the background for this study.

## Related Studies

To clarify the position of the current study in the history of cognitive science, we briefly introduce the approach of cognitive modeling that the current study takes and the models of emotional states that the current study targets.

### Cognitive model and cognitive architecture

To define the parameter set for individuals, it is useful to assume a general cognitive architecture. Among the various ones, ACT-R (Adaptive Control of Thought-Rational; Anderson, 2007) and Soar (Laird, Newell, & Rosenbloom, 1987) are representative. The current study especially focuses on ACT-R, a widely used cognitive architecture that is flexible and scalable for modeling various cognitive processes, including memory, attention, and decision-making.

[1] This study deals with these terms interchangeably.

Although cognitive architectures provide standardized functions to simulate human cognitive processes, parameters need to be adjusted for each task and individual. In model building, parameter fitting is essential to improve the accuracy and reliability of the model. However, there is no standardized method for parameter estimation in cognitive model researches.

In this study, we employed an original algorithm similar to the gradient descent that appropriately narrows the parameter search range to the entire experimental data. This approach aims to efficiently and accurately estimate model parameters for each individual. It is particularly effective in constructing models with large amounts of data and multidimensional parameter spaces.

### Cognitive model and emotional states

Research on the interaction between cognition and emotion has long been conducted in various fields. Widely known theories include the somatic marker hypothesis (Damasio, 1994) and the mood congruency effect (Bower, 1981). The former indicates the strong connections between emotional states and decision-making, and the latter explains that positive memories are evoked when we are in a positive mood and negative memories are evoked when we are in a negative mood. These theories show that emotional context plays an important role in human decision-making and cognitive processing.

In particular, negative emotions are known to induce emotional behaviors such as ruminative thinking (Lyubomirsky, Caldwell, & Nolen-Hoeksema, 1998) and mind-wandering (Smallwood & Schooler, 2006). Memory recall during these cognitive tasks is also related to anxiety about future events (LeDoux, 1998). There are large individual differences in their anxiety and risk aversion tendencies. Prominent anxiety disorders are known to exhibit delayed responses due to significant anxious feelings. Thus, emotions and cognition interact in a complex manner and are expressed as various behaviors.

As an attempt at emotion modeling, ideas of cognitive modulator in which emotions adjust the cognitive parameters according to the situation have been proposed (Ritter, 2009). Furthermore, in recent years, the inclusion of an emotion module into the concept of the common model of cognition has been discussed, and research toward an integrated understanding of emotion and cognition has been progressing (Rosenbloom et al., 2024; van Vugt & van der Velde, 2018; van Vugt, Taatgen, Sackur, & Bastian, 2015; Juvina, Larue, & Hough, 2018). In these studies, approaches such as adding new modules or extending existing cognitive architecture such as ACT-R have been taken to represent emotions. In contrast to these approaches, the present study examines the existing parameters of ACT-R and their correspondence to emotions to determine which emotional states can be represented by the current ACT-R or which parameters are needed for future extension of the architecture.

## Model

This study deals with a simple memory task to estimate cognitive parameters related to emotional states. Memory is a basic cognitive function used in a wide range of cognitive tasks. In addition, memory is closely related to emotional states as discussed in the previous section.

There is a discussion dividing human memory errors into several types, and the main categories are *commission errors*, in which a false memory is reproduced, and *omission errors*, in which a memory that should be recalled is not recalled (Schacter, 2002). In this study, we use a model to simulate such two types of errors and map them to human memory tasks.

### Task

A simple digits recall task was employed because it is easy to model and the difficulty of the task can be reasonably adjusted. In this task, participants are presented with a randomly generated number sequence for a certain period of time. After the number sequence disappears, the participant is required to recall the number within a certain allotted time.

### Representation and Process

The grouped model included in ACT-R Tutorial Unit 5 (Bothell, 2022) is employed. This model divides a sequence of numbers into groups and stores each number in terms of its position in the group and its position within the group. Specifically, a sequence of numbers such as "123456789" is divided into groups such as (123) (456) (789), and "1" is stored as "the first number in the first group." This structure is derived from the memory structure in the model of serial positional memory (Anderson, Bothell, Lebiere, & Matessa, 1998).

To recall the number sequence, the model shifts the focus digits or the focus groups from left to right. That is, at the beginning of the task, the model attempts to retrieve from memory the first number in the first group. Next, it searches for the second and third numbers, and if it cannot recall the number corresponding to each position, it moves on to the next number in the group. The process is repeated to move the focus in the end of the sequence.

When retrieving a number at each position in a sequence, the activation is calculated for the entire number in the memorized sequence and the number with the highest activation is selected for recall. The activation($A_i$) of a number $i$ in memory is calculated by the following formula

$$A_i = \sum_l PM_{li} + \varepsilon \tag{1}$$

where $l$ represents the number of conditions in the retrieval request. There are two conditions in the retrieval requests of this model. One is the group, and the other is the position in the group. $M_{li}$ indicates the similarity between the retrieval condition and the corresponding attribute of the target digit $i$, and is set to 0 when the condition matches exactly and to 1 when it does not. If the two groups have similar attributes, the similarity defined in the model is assigned. In this model, a similarity of 0.5 is assigned to adjacent numbers and groups. Further, the similarities are weighted by $P$, which is set as a global parameter *mp* (mismatch penalty) within ACT-R. If this value is relatively small, the model retrieves memory items that only have a small similarity with the retrieval requests. Otherwise, it will strictly retrieve an item that matches the request. The retrieval of the wrong number happens by the function of $\varepsilon$, which is a temporal noise component and set by a global parameter called *ans* (activation noise s).

Thus, equation 1 shows that when *mp* is set small and *ans* is set large, the probability of a commission error is high. Specifically, the group model shows the commission error as a swap in the order of the numbers or the recall of different numbers. On the other hand, an omission error occurs when the activation of all memory items falls below a threshold determined by the parameter called *rt* (retrieval threshold). This error is observed in the form of a number not being recalled.

### Parameter fitting

The model parameters are adjusted to fit the experimental data. In this study, we use the following index and procedure to explore best fit parameters for each individual participant.

**Index** This study measures the degree of agreement between the experimental data and the model output based on Histogram Intersection (HI; Swain & Ballard, 1991) of edit distance[2] between the recalled and the presented number sequences. Since the frequencies were different between the experimental data and the model output, they were normalized so that the sum of the frequencies was 1 for the comparison.

**Fitting process** To reproduce the commission and omission errors in the responses, the *mp* and *rt* that best fit the individual experimental data are searched. Since there are countless appropriate ranges and combinations of parameters, we first roughly specify the range of parameters, and then search within that range as follows:

1. Determine the initial median and range of *mp* and *rt*.
2. Generates candidates with shifted medians and ranges for each parameter. The shifted median is the current value plus $+0.5$, $+0$, or $-0.5$, and the shifted range is the current value multiplied by $*1.2$, $*1.0$, or $*0.8$.
3. For each median and range combination ($3^4$), discretize the parameter values into 10 steps.
4. For each combination of *mp* and *rt*, we run the model with 100 parameters (10 steps of *mp* x 10 steps of *rt*) and construct a histogram of edit distances. In addition, a similar histogram was constructed for each participant's responses. For each participant's histogram, we identify the histogram of the model that best matches and compute the sum for all participants for that HI.
5. Execute the above 4 for $3^4$ combinations of the currently set median values and ranges of *rt* and *mp*. Compare the sum of the largest HIs in that combination to the largest HI in the past median and range settings. If a value exceeding the sum of past HIs is obtained from the combination of the current median and range, the median and range at that point are used as the value of the range for the next step.
6. Repeat the above until the maximum value of the sum of HI is no longer updated.

The above procedure identifies the parameter range that maximize the fitting for the entire experimental data. Among them, the parameter with the highest HI for each individual is selected as the individual parameter.

## Experiment 1

We collected human data on the digits recall task. Based on the collected data, we fitted a model to simulate the experimental task. Regarding the model parameters for each individual obtained as a result, we examined the correspondence between the personal traits of the experiment participants and their emotional states.

### Method

**Participants** Fifty participants recruited through the crowdsourcing service Lancers.jp participated in the experiment. They were paid 100 yen as compensation for their cooperation in the experiment.

**Materials** To obtain the participants' personal attributes and internal state during the task, they answered questionnaires after completing the task. The items included age, gendered, educational background, physical conditions (1. bad – 5. good), self-evaluation of memorization ability (1. very bad – 6. very good), and the Japanese version of PANAS (Positive and Negative Affect Schedule; Watson, Clark & Tellegen; Sato & Yasuda, 2001; Kawahito, Otsuka, Kaida, & Nakata, 2022), which consists of 20 items related to positive affects and 20 items related to negative affects (6 points scale).

**Procedure** The entire experiment procedure was executed online. First, the participants visited a site located in the authors' server from the link provided in the crowdsourcing site. The website displays information about the task and points to note. After reading the instructions, participants entered their user ID of the crowdsourcing and moved to the assignment screen.

In the digits recall task, a number sequence was presented to the participants on a monitor for 2 seconds. After the presentation, the participants entered the memorized number sequence into the text box on the monitor using the keyboard within a 20-second response time. When the answer was completed, the participants could immediately move on to the next digits by pressing the enter key.

[2] python-Levenshtein package (https://pypi.org/project/python-Levenshtein/) was used.

Table 1: Attributes and base performance of the task

| | Experiment 1 Mean (SD) | Experiment 2 Mean (SD) |
|---|---|---|
| Age | 43.31 (8.52) | 45.42 (10.26) |
| Physical condition | 3.57 (0.91) | 3.65 (1.01) |
| Academic background | 3.80 (0.71) | 3.60 (0.85) |
| Memory ability | 2.39 (0.73) | 2.57 (0.90) |
| Positive (Pre) | - | 30.50 (9.27) |
| Positive (Post) | 27.18 (7.18) | 25.38 (9.99) |
| Positive (Increase) | - | -5.13 (7.65) |
| Negative (Pre) | - | 17.64 (7.21) |
| Negative (Post) | 30.49 (6.55) | 33.75 (10.71) |
| Negative (increase) | - | 16.11 (9.56) |
| State anxiety (Pre) | - | 44.94 (9.47) |
| State anxiety (Post) | - | 58.32 (8.88) |
| State anxiety (increase) | - | 13.38 (9.98) |
| Trait anxiety | - | 48.93 (12.57) |
| Arousal | - | 0.64 (0.11) |
| Valence | - | 0.40 (0.09) |
| Edit distance | 3.18 (1.00) | 2.19 (0.90) |
| Missing digits | 0.04 (0.07) | 0.54 (0.88) |

After completing the task 30 times, the participants answered a questionnaire regarding personal attributes and affective states. After completing the answers, the experiment ended.

## Results

**Data** One of the 50 participants was excluded from the analysis because data could not be obtained correctly due to a flaw in the experimental environment. The answered gender by the participants reveals 13 women and 36 men were included in the data. The other attributes of the data are summarized in the second column of Table 1. The performance of the memory task were quantified by the edit distance and number of missing digits between the presented and the answered sequences.

**Fitting results** Using the procedure shown in the Model section, we systematically searched for the median value and range of each parameter. In this estimation, the initial values of the mean and range were set as follows: *mp* median: 1.0, *mp* range: 2.0, *rt* median: $-1.0$, *rt* range: 4.0. These settings reflected the preliminary experiments. As outputs of this estimation, the parameter sets maximizing the HI of the memory task performance between the model and individual participants were selected. In this process, the histogram of the 100 simulation runs was created. The intersection of this histogram with the participant's histogram, which consisted of 30 trials, was calculated.

The parameter search was repeated five times to consider random factors when selecting the same HI parameter sets during the estimation process. The results are shown in Table 2. Based on the parameter range obtained in the fourth trial, which achieved the highest fit among the five simulations, we selected the parameters that best fit each individual.

Table 2: Fitting result of experiment 1

| | HI (%) | *mp* median | *mp* range | *rt* median | *rt* range | Num of updates |
|---|---|---|---|---|---|---|
| Trial 1 | 48.67 | 1.50 | 0.82 | -1.00 | 1.31 | 5 |
| Trial 2 | 48.46 | 1.50 | 0.82 | -1.00 | 1.31 | 5 |
| Trial 3 | 48.36 | 1.50 | 0.82 | -1.00 | 1.31 | 5 |
| Trial 4 | 61.64 | 1.00 | 0.21 | -0.50 | 0.43 | 10 |
| Trial 5 | 48.42 | 1.50 | 0.82 | -1.00 | 1.31 | 5 |
| Mean | 51.11 | 1.40 | 0.70 | -0.90 | 1.13 | 6 |
| Median | 48.46 | 1.50 | 0.82 | -1.00 | 1.31 | 5 |
| Max | 61.64 | 1.50 | 0.82 | -0.50 | 1.31 | 10 |
| Min | 48.36 | 1.50 | 0.82 | -1.00 | 1.31 | 5 |

**Correlation between parameters and subjective ratings** We analyzed the correlation between the model parameters for each individual obtained through the above procedure and items of questionnaires (attributes and affective states). The results showed a significant positive correlation of 0.326 ($n = 49$, $p < .05$) between age and *rt*, and 0.360 ($n = 49$, $p < .05$) between physical condition and *rt*. However, no significant correlation was found between the parameters and PANAS scores. When we calculated the Spearman correlation coefficient with the items consisting PANAS, we found a significant correlation of 0.291 only between *mp* and the negative emotion item "afraid ($M = 3.47$, $SD = 1.60$)."

### Discussion

Table 2 confirms that the method proposed in this study can roughly identify the parameter search range from experimental data. However, the overall average fitting value was not high. We speculate that this is because the data included participants who did not fit into the assumed model (grouped recall). In addition, we could not observe correlations between the parameters and PANAS score. A possible reason why no significant correlation was observed was that there was not enough variance in emotional states between participants.

## Experiment 2

) Considering the limitations of Experiment 1, we set up a situation in which emotional states were expected to be diversified. Specifically, we presented emotion-arousing during the task. Furthermore, we added questions about the participants' emotional states that were more related to the cognitive tasks. We used the STAI (State-Trait Anxiety Inventory; Spielberger, Gorsuch, & Lushene, 1970; Nakazato & Mizuguchi, 1982), which is known as a common anxiety scale supposed to affect cognitive process (LeDoux, 1998). Furthermore, in order to clarify the causal relationship between emotions and task performance, we posed a questionnaire about their emotional state before and after the digits recall task. Furthermore, we included dummy questions to eliminate participants who did not fit the model as suggested in Experiment 1. This study was approved by the ethical committee of the author's affiliated institution.

### Method

**Participants** We recruited 100 participants through a crowdsourcing site (Lancers.jp) and paid them 400 yen as

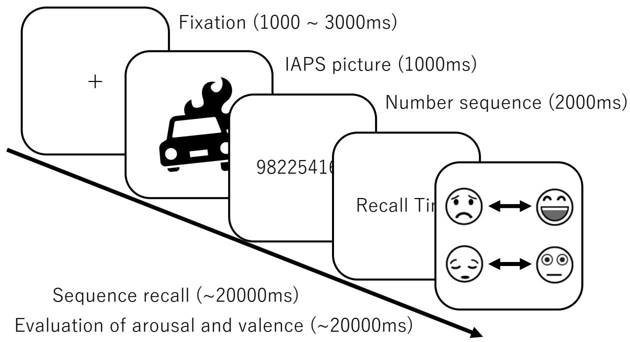


Figure 1: Experiment 2: digits recall task

compensation. To obtain more reliable correlations with high statistical power, Experiment 2 increased the number of participants. We also paid a higher compensation than Experiment 1 because the time required for the task increased, as described below.

### Materials

**Digits recall task** The task was generally the same as in Experiment 1. However, in Experiment 2, the number sequence presented was nine digits to get closer to the original model presented in ACT-R Tutorial Unit 5. In addition, an emotion-arousing stimulus was introduced before the presentation of the number sequence, and an evaluation phase for recall accuracy and emotional valence was introduced after the answer to the number sequence. Furthermore, the number of trials per participant was increased from 30 to 40. The flow of one trial is shown in Figure 1. After the overall digits recall task was completed, the participants were asked to rate their affective states using the Affective Slider (Betella & Verschure, 2016).

**IAPS dataset** The International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 2008)) was used as the emotion-arousing stimuli. This dataset is a standard dataset designed and developed by the National Institute of Mental Health (NIMH) for the purpose of research on emotions and attention. It contains approximately 1,000 color photographs, with a wide range of content. Each image was rated on a 9-point scale by participants in multiple studies for valence, arousal and sense of dominance using the Self-Assessment Manikin (SAM; Bradley & Lang, 1994).

In this experiment, we attempted to introduce a large variance of the participants' emotional state by randomly presenting 20 positive/high-arousal pictures ($M_{valence}$ = 7.57, $SD_{valence}$ = 1.63, $M_{arousal}$ = 6.66, $SD_{arousal}$ = 2.17) and 20 negative/high-arousal pictures ($M_{valence}$ = 1.62, $SD_{valence}$ = 1.18, $M_{arousal}$ = 6.96, $SD_{arousal}$ = 2.18) to participants before the presentation of a number sequence.

**Questionnaires** In addition to the same items as in Experiment 1, state anxiety and trait anxiety were measured using the STAI. In order to measure changes in emotional states before and after the task, participants were asked to answer the state anxiety items on STAI and the items on PANAS before the entire recall task (pre-questionnaire). After the recall task, participants were asked to answer the same items as in Experiment 1, as well as the trait anxiety items on the STAI (post-questionnaire).

In addition, to exclude data from the participants who were distracted by the experiment, dummy questions were included in the PANAS and STAI items. The dummy questions were "Tired" and "Not Enjoying," and participants were asked to select a specified score for those items.

**Procedure** The process was basically the same as in Experiment 1. However, on the experimental page, participants were first shown a consent confirmation document, which stated that emotional harm stimuli would be presented to them, and after carefully reading the document, they decided whether or not to participate in the experiment. After consenting, participants were directed to a page where the overall flow of the experiment was explained, after which they entered their crowdsourcing user ID and answered pre-questionnaires. After completing the 40 recall tasks, participants answered a post-questionnaire.

## Results

**Data** For the analysis, we excluded the data of 28 participants who did not correctly answer the dummy questions. We performed fitting using the resting data of 72 participants and analyzed the correlation between the obtained individual model parameters and questionnaire items (attributes and emotion evaluation scores). The third column of Table 1 shows the mean and standard deviations of those items and task performance obtained through this experiment. By comparing with Experiment 1, we observed a decrease in the positive affects (27.18 to 25.23), an increase in the negative affects (30.49 to 33.75), and a reduction in edit distance (3.18 to 2.19) as consistent with the addition of the experiment procedure. More importantly, the standard deviation of affect ratings increased from those of Experiment 1 (7.18 to 9.99 in positive, 6.55 to 10.71 in negative) as intended.

**Fitting results** We used the original grouped model shown in ACT-R Tutorial Unit 5. The same procedures as in Experiment 1 were used to narrow down the parameter range and identify individual parameters. However, in Experiment 2, the median and initial range value of each parameter were unified to 1.0 to eliminate arbitrariness in the search range. The parameters with the highest HI for each individual were selected as individual parameters in the process of narrowing down the parameter range.

The results are shown in Table 3. The change in the median and the reduction in the range suggest that the proposed method narrows the parameter search range. Furthermore, the table shows that the overall fitting accuracy is improved by 13.36% on average compared to Experiment 1, suggest-

Table 3: Fitting result of experiment 2

| | HI (%) | *mp* median | *mp* range | *rt* median | *rt* range | Num of updates |
|---|---|---|---|---|---|---|
| Trial 1 | 53.41 | 1.50 | 0.96 | -1.00 | 1.15 | 4 |
| Trial 2 | 67.47 | 1.00 | 0.13 | -0.50 | 0.12 | 14 |
| Trial 3 | 67.06 | 1.00 | 0.17 | -0.50 | 0.19 | 11 |
| Trial 4 | 67.39 | 1.00 | 0.13 | -0.50 | 0.19 | 13 |
| Trial 5 | 67.04 | 1.00 | 0.19 | -0.5 | 0.16 | 12 |
| Mean | 64.47 | 1.10 | 0.32 | -0.60 | 0.36 | 10.80 |
| Median | 67.05 | 1.00 | 0.18 | -0.5 | 0.19 | 11.50 |
| Max | 67.47 | 1.50 | 0.96 | -0.50 | 1.15 | 14.00 |
| Min | 53.41 | 1.00 | 0.13 | -1.00 | 0.12 | 4.00 |

Table 4: Correlation analysis for experiment 2

| | HI | *mp* | *rt* |
|---|---|---|---|
| Age | 0.076 | 0.085 | -0.159 |
| Gender | 0.069 | 0.047 | -0.118 |
| Academic background | -0.035 | -0.059 | 0.091 |
| Physical condition | -0.039 | 0.072 | -0.111 |
| Memory ability | 0.080 | 0.007 | -0.030 |
| Positive (Pre) | -0.006 | -0.218 | 0.213 |
| Positive (Post) | -0.049 | -0.020 | 0.075 |
| Positive (Increase) | -0.057 | 0.237* | -0.161 |
| Negative (Pre) | -0.158 | 0.133 | -0.136 |
| Negative (Post) | 0.075 | 0.082 | -0.126 |
| Negative (Increase) | 0.203 | -0.009 | -0.039 |
| State anxiety (Pre) | 0.065 | 0.305** | -0.287* |
| State anxiety (Post) | 0.134 | 0.076 | -0.103 |
| State anxiety (Increase) | 0.058 | -0.222 | 0.181 |
| Trait anxiety | 0.196 | 0.230 | -0.061 |
| Arousal | -0.013 | -0.079 | 0.097 |
| Valence | -0.007 | 0.053 | -0.065 |
| Edit distance | -0.616* | -0.511*** | 0.233* |
| Missing digits | -0.331* | -0.044 | 0.078 |

$*p < .05, **p < .01, ***p < .001$

ing the revision of the experimental procedure worked as intended.

**Correlation between parameters and subjective ratings**
The model parameters that produced the highest HI through five estimations were selected as the individual parameters, and the Pearson correlation between the obtained parameters and attributes was analyzed (Table 4).

A significant correlation was found between the state anxiety score (pre) and the *mp* and *rt* parameters of the model ($n = 72$, $p < .05$). In addition, a significant positive correlation was found between the increased amount of positive scores before and after the task and the *mp* parameters of the model ($n = 72$, $p < .05$).

## Discussion

In this experiment, we improved the method to obtain more precise data relating to memory performance and emotion changes. As Tables 1 and 4 indicate, this improvement succeeded. In addition, we observed the results showing that the higher the state anxiety, the higher the *mp* and the lower the *rt*. This suggests that individuals with high state anxiety are less likely to make memory errors (both commission and omission errors). In other words, this suggests that they tend to be able to recall memories more accurately.

Furthermore, participants whose positive scores decreased before and after the task tended to have smaller *mp*. Table 1 shows that the average decrease of the positive scores across was 5.13 points. From this, we can speculate that the presentation of images affected the decrease in positive emotions. The results suggest that participants with particularly low *mp* (with a tendency to make commission errors) tended to experience a more significant decrease in positive emotions. However, as it is possible that a decrease in positive emotions caused a decrease in *mp*, future research needs to examine the causal relationship between memory parameters (e.g, *blc*: base level, *bll*: decay rate) and emotion changes.

## Conclusion

The two experiments examine the relation between parameters in cognitive model and emotional states. Specifically, the parameters fitting of the memory model was performed with data by individual participants, and the correspondence with personal attributes and subjective emotional states was examined. As a result of Experiment 2, in which the experimental method was improved, the link between the cognitive model and emotional states were obtained. In other words, it was shown that individuals with higher state anxiety were less likely to make both commission and omission errors. Furthermore, a correlation was observed between decreased positive emotions and decreased *mp*. These suggest that emotional states such as fear and anxiety can be expressed to some extent using ACT-R parameters.

The limitation of this study is the accuracy of parameter estimation. Given the low correlations in Table 4, it is thought that the introduction of new model parameters and the expansion of the model will be required to further investigate the relationship between personal attributes or emotional states and cognition, as suggested by Rosenbloom et al. (2024)

Furthermore, in order to concretize the complex aspects of personal attributes and emotional states, it is important for future research to focus on expanding the model. Specifically, it will be necessary to clarify the causal relationship between changes in emotional states and cognitive tendencies, as well as to design and verify new parameters to appropriately express changes in emotional states.

By addressing such technical issues step by step, our approach will reach various practical applications. The parameters estimated in this study, such as *mp* and *rt*, are general and can be applied to other tasks. Therefore, by using individual-specific parameters, it becomes possible to predict the behavior of participants in tasks other than the current one. In particular, support using models externalizing internal stats is believed to be useful for individuals suffering from anxiety-related disorders (LeDoux, 1998).

## References


Anderson, J. R. (2007). *How can the human mind occur in the physical universe?* Oxford University Press.

Anderson, J. R., Bothell, D., Lebiere, C., & Matessa, M. (1998). An integrated theory of list memory. *Journal of Memory and Language*, *38*(4), 341-380. doi: https://doi.org/10.1006/jmla.1997.2553

Betella, A., & Verschure, P. F. M. J. (2016, 02). The affective slider: A digital self-assessment scale for the measurement of human emotions. *PLOS ONE*, *11*(2), 1-11. doi: 10.1371/journal.pone.0148037

Bothell, D. (2022). Unit 5: Activation and context, act-r tutorial [Computer software manual]. (Accessed online or distributed as part of the ACT-R tutorial package)

Bower, G. H. (1981). Mood and memory. *American psychologist*, *36*(2), 129. doi: 10.1037/0003-066X.36.2.129

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry*, *25*(1), 49-59. doi: 10.1016/0005-7916(94)90063-9

Damasio, A. R. (1994). Descartes ' error: Emotion, reason, and the human brain. *Grosset/Putnam*.

Juvina, I., Larue, O., & Hough, A. (2018). Modeling valuation and core affect in a cognitive architecture: The impact of valence and arousal on memory and decision-making. *Cognitive Systems Research*, *48*, 4–24. doi: 10.1016/j.cogsys.2017.06.002

Kangasrääsiö, A., Jokinen, J. P. P., Oulasvirta, A., Howes, A., & Kaski, S. (2019). Parameter inference for computational cognitive models with approximate bayesian computation. *Cognitive Science*, *43*(6), e12738. doi: 10.1111/cogs.12738

Kawahito, J., Otsuka, Y., Kaida, K., & Nakata, A. (2022). Reliability and validity of the japanese version of 20-item positive and negative affect schedule. *Hiroshima Psychological Research*, *11*, 225–240. doi: 10.15027/32396

Laird, J. E., Newell, A., & Rosenbloom, P. S. (1987). Soar: An architecture for general intelligence. *Artificial Intelligence*, *33*(1), 1-64. doi: 10.1016/0004-3702(87)90050-6

Lang, P., Bradley, M., & Cuthbert, B. (2008). *International affective picture system (iaps): Affective ratings of pictures and instruction manual* (Technical Report No. A-8). Gainesville, FL: University of Florida.

LeDoux, J. E. (1998). *The emotional brain: The mysterious underpinnings of emotional life*. Simon and Schuster.

Lyubomirsky, S., Caldwell, N. D., & Nolen-Hoeksema, S. (1998). Effects of ruminative and distracting responses to depressed mood on retrieval of autobiographical memories. *Journal of personality and social psychology*, *75*(1), 166. doi: 10.1037/0022-3514.75.1.166

Nakazato, K., & Mizuguchi, T. (1982). Development and validation of japanese version of state-trait anxiety inventory : A study with female subjects. *Japanese Journal of Psychosomatic Medicine*, *22*(2), 107-112. doi: 10.15064/jjpm.22.2_107

Ritter, F. E. (2009). Two cognitive modeling frontiers. *Information and Media Technologies*, *4*(1), 76-84. doi: 10.11185/imt.4.76

Rosenbloom, P., Laird, J., Lebiere, C., Stocco, A., Granger, R., & Huyck, C. (2024). A proposal for extending the common model of cognition to emotion. In *Proceedings of the 22th international conference on cognitive modeling.*

Sato, A., & Yasuda, A. (2001). Development of the japanese version of positive and negative affect schedule (panas) scales. *The Japanese Journal of Personality*, *9*(2), 138-139. doi: 10.2132/jjpjspp.9.2_138

Schacter, D. L. (2002). *The seven sins of memory: How the mind forgets and remembers*. HMH.

Smallwood, J., & Schooler, J. W. (2006). The restless mind. *Psychological Bulletin*, *132*(6), 946–958. doi: 10.1037/0033-2909.132.6.946

Spielberger, C. D., Gorsuch, R. L., & Lushene, R. E. (1970). *Stai manual for the state-trait anxiety inventory ("self-evaluation questionnaire")*. Consulting Psychologists Press.

Swain, M. J., & Ballard, D. H. (1991). Color indexing. *International journal of computer vision*, *7*(1), 11–32. doi: https://doi.org/10.1007/BF00130487

van Vugt, M. K., Taatgen, N. A., Sackur, J., & Bastian, M. (2015). Modeling mind-wandering: a tool to better understand distraction. In *Proceedings of the 13th international conference on cognitive modeling.*

van Vugt, M. K., & van der Velde, M. (2018). How does rumination impact cognition? a first mechanistic model. *Topics in Cognitive Science*, *10*(1), 175-191. doi: 10.1111/tops.12318

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The panas scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070. doi: 10.1037/0022-3514.54.6.1063